Assignment2

STAT380

Due Date Monday, 6th November 2023 by 11:59 pm

###  
library(tree)  
###  
library(ISLR)  
#attach(Carseats)  
library(rattle)

## Warning: package 'rattle' was built under R version 4.0.5

## Loading required package: tibble

## Loading required package: bitops

## Rattle: A free graphical interface for data science with R.  
## Version 5.5.1 Copyright (c) 2006-2021 Togaware Pty Ltd.  
## Type 'rattle()' to shake, rattle, and roll your data.

library(rpart.plot)

## Loading required package: rpart

library(RColorBrewer)  
library(partykit)

## Loading required package: grid

## Loading required package: libcoin

## Loading required package: mvtnorm

The data set `Carseats’ is a simulated data set containing sales of child car seats at 400 different stores of a specific departmental store over a period of a few months. For the different activities in this assignment, we consider a categorical binary variable, that we call ‘High\_Sales’. We consider the sales amount is high, i.e., High\_Sales=1, if the number of car sets that are sold is greater than 8 in the particular store.

# Problem A

### A1. (3 points) Create a new binary categorical variable called High\_Sales' which is defined as follows: $ \text{High\_Sales}='High' \text{ if }Sales’>8 $ and $ =0’Low’ `Sales’ $

### A2. (2 points) Add the new variable to the dataset `Carseats’.

data(Carseats)  
names(Carseats)

## [1] "Sales" "CompPrice" "Income" "Advertising" "Population"   
## [6] "Price" "ShelveLoc" "Age" "Education" "Urban"   
## [11] "US"

### A1.  
  
  
### A2.

### A3. (5 points) Build a classification tree where the response is ‘High\_Sales’ and the predictors are all the other variables except ‘Sales’ and ‘High\_Sales’.

### A3.

### A4 (5 points) Plot the fitted tree

# A4 Plot the regression tree  
  
#you may use fancyRpartPlot(fit\_object, caption = NULL) # Nicer plot but need libraries `RColorBrewer', `rattle' and `rpart.plot'

## Training and Testing Set

### A5.1. ( 1+4+2 =7points) Now, set a seed. Create a training set and a testing set , use a training set (70% in the training Set and 30% in test set). Print the dimension of the Training and Testing set

#### A5.1:

### A5.2. (5+3=8 points) Fit the Classification Tree in the Training set and Plot the tree

### A5.2.  
  
  
  
# plot the fitted tree you may use: fancyRpartPlot(fit\_object, caption = NULL)

### A6.1(5+2=7 points) Print the summary, cross-validated cp values and plot the cp values. Comment on the Error Rate in the validation part.

A6.2 (3 points) Identify an optimal value for complexity parameter `cp’.

Note: cp = “value” is an assigned numeric value that will determine how tall a tree is to be grown the smaller value (closer to 0) leads to the larger the trees. The default value is 0.01.

### A6.1   
  
  
### A6.2  
#bestcp <-fit\_train$cptable[which.min(fit\_train$cptable[,"xerror"]),"CP"]

### A7. (5 points) Obtain a Pruned tree based on to the optimal value of `cp’ that you have obtained in A6.

### A7.  
  
## Pruned tree

### A8.1 (3 points) Predict on the Testing set with the pruned tree

### A8.2 (3 points ) Predict on the Testing set with the entire tree fitted using the training set

### A8.1  
  
  
### A8.2

### A9.1 (2 points) Create the classification tables of the errors using the Predicted values from the pruned tree

### A9.2 (2 points) Create A classification Tables of the errors using the Predicted values from entire tree fitted using the training set

#A9.1  
  
#A9.2  
  
## Write a Conclusion of your finding

### A10. (5 points) Compare the classification performance of the tree and the pruned tree.

#Problem B (Fitting Regression Trees)

### We will use the regression trees for the Boston Housing data

Load the data from the github course page using: BostonH<-read.csv(url(“<https://raw.githubusercontent.com/subhadippal2019/STAT380UAEU/main/BostonHousing.csv>”))

BostonH<-read.csv(url("https://raw.githubusercontent.com/subhadippal2019/STAT380UAEU/main/BostonHousing.csv"))  
names(BostonH)

## [1] "CRIM" "ZN" "INDUS" "CHAS" "NOX" "RM"   
## [7] "AGE" "DIS" "RAD" "TAX" "PTRATIO" "LSTAT"   
## [13] "MEDV" "CAT..MEDV"

### B1 ( 4+1=5 points ) Split the data in Training and Testing Set. Use a 60%/40% split for the Training and Testing Set. Print the dimension of the Testing and the Training set.

#### A5.1:  
set.seed(1234)  
 #

### B2.( 5 points )

Fit a regression tree on the Training Set using the MEDV', the median price of houses in a region, as the response variable while all the other variables EXCEPT theCAT..MEDV’ as the covariates. Display/plot the fitted tree.

### B2.  
  
# plot fitted tree# You may use fancyRpartPlot(fitted\_object, caption = NULL)

### B3.( 3 points ) Print the summary and the tables containig the crossvalidated `cp' and plot the `crossvalidatedcp’. Comment on the Error Rate in the validation part. (summary, printcp, plotcp)

( 2 points ) Identify an optimal value for the complexity parameter `cp’.

### B3.

## B4.( 2+3=5 points ) Find the optimal value of `cp’ and Prune the regression tree.

## B4.  
#bestcp <-fit\_train$cptable[which.min(fit\_train$cptable[,"xerror"]),"CP"]

## B5.1 ( 3+2=5 points ) Predict on the Testing set with the pruned tree. Plot the predicted values vs the response values in the test set.

## B5.2 ( 3+2=5 points ) Predict on the Testing set with the Entire tree fitted to the training set. Plot the predicted values vs the response values in the test set.

### B5.1  
##Predict:   
  
  
##Plot  
  
  
  
### B5.2  
##Predict:   
  
  
##Plot

### B6 ( 4+4+2=10 points ) Calculate the MSE for prediction using both the trees, the pruned tree and the entire tree based on the Training set. compare their MSE. Comment on your findings.

### B6   
#mean((Predicted\_response - Response\_in\_Test )^2)  
#Calculate the MSE for prediction using both the trees  
  
  
 #Compare their MSE. Comment on your finding.